2017

Economical Approach To Design Of Passive Distributed Antenna System

Rohan A. Shah
Lehigh University

Economical Approach to Design of Passive Distributed Antenna System

By

Rohan A. Shah

A Thesis

Presented to the Graduate and Research Committee

of Lehigh University

in Candidacy for Degree of

Master of Science

in

Electrical Engineering

Lehigh University

Dec 2017

Certificate of Approval

This thesis is accepted and approved in partial fulfillment of the requirements for the Master of Science.

Date

Prof. Shalinee Kishore
Thesis Advisor

Prof. Chengshan Xiao
Chairperson of Department

Contents

List of Figures

Abstract

With increase in the indoor usage of communication, there has been increase in the need for optimal design of mobile coverage for buildings with a lot of users. Cellular service companies had been pushing the limits with their macro-cell approach however, with the advent of 4G LTE and their higher frequency use, the penetration inside the buildings adds to their troubles. A Distributed Antenna System(DAS) extends the mobile coverage from the base station to distributed antennas through a network topology of coaxial cables and power splitters. Though the solution of DAS would solve the problem of mobile coverage but the total cost of ownership is a major obstacle. To reduce the total cost of ownership for enterprises, the need to optimize the design arises. This work researches the use of a popular computational method to optimize the design of in-building passive distributed antenna system with iterative improvements. The application of Particle Swarm Optimization(PSO) to the design problem reduces the cost of the deployment and also provides a quicker solution than brute force search. The model converges on an optimal design solution and stops execution at the stop criteria which has been empirically proven as appropriate. To make the design topology compatible with the particle swarm optimization, tree topology of passive DAS is converted to prufer code. This allows the PSO algorithm to traverse through different solutions in the Euclidean space. The current optimization methods have only been applied to either optimizing the length of the cable or the equipment selection. This approach provides optimization for the complete deployment of passive DAS. Test results of the model show that we achieve the design way more quickly due to reduction in the complexity and the cost is reduced for the deployment due to optimal design.

Chapter 1

Introduction

The evolution of mobile communication technology with the usage of higher frequency bands has posed new limitations. Penetration of these high frequency radio waves inside building is severely hindered. According to a research carried out by Cisco, smart phones require 24 times the amount of data bandwidth of regular phones, and tablets are even more demanding. They require on average, 122 times more data compared to a regular phone. Figure 1.1 illustrates the expected growth of mobile data usage in the next 5 years. This has led to increase in usage of mobile data, growing exponentially over the past decade with most of the traffic generated indoors[14]. Statistically, the 80% of the mobile data is generated within indoor propagation environments. This would continue to grow with further deployments and evolution of the mobile technology. To make the task even more daunting, use of data is becoming increasingly localized to areas with a high user density, many of them using multiple devices at the same time. Large office buildings, concentrated residential areas, public buildings like subway stations, airports, sport arenas or convention centers require infrastructure solutions that provide best efficiency, while at the same time resolving coverage and capacity challenges.

The deployment of 4G in the last 5 years has added to this limitation. The indoor coverage of mobile networks is difficult due to the signal losing its strength in penetration

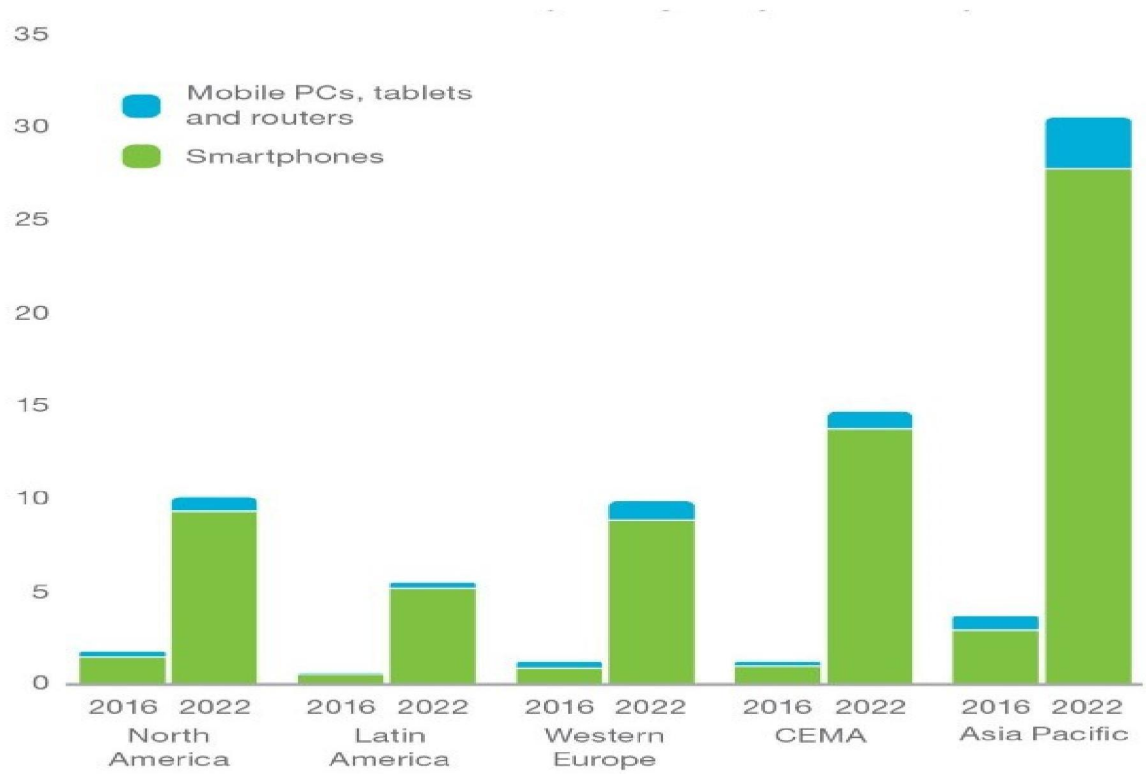

Figure 1.1: Global Mobile Data Traffic in *Exabytespermonth*

through concrete walls or reflection of glass panels. The loss of signal strength depends on the construction material used. Due to this, the conventional Centralized Antenna Systems(CAS) deployments provides deteriorated or no coverage. Network infrastructure, both in-building and outdoors, must offer adequate coverage and bandwidth to handle and transport this huge amount of data. Providing reliable signal coverage indoors with higher data rates and better quality transmission has become important for the mobile communication operators. These challenges have given way to the new methods to meet these rising indoor traffic demands. One of the widely accepted new way is the usage of In-building Distributed Antenna Systems(DAS). Well designed Distributed Antenna Systems, both in-building and outdoors, provide high quality but cost effective coverage solutions for any given environment. They provide coverage in locations where (additional) cell site towers are simply not a viable option[18]. With a wide scale deployment of distributed antenna systems, another major consideration would be the cost of the deployment and the

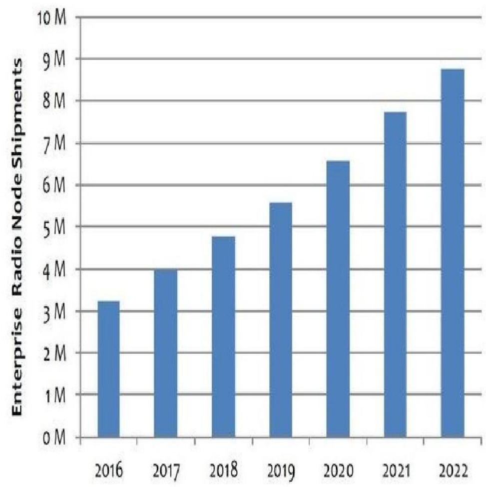

Figure 1.2: Growth of Enterprise DAS

robustness of the network.

The specific focus of this work is on near optimal design of in-building DAS that provides us with the best topology with least possible cost of equipments and installation in DAS which meets functional requirements.

Chapter 2 covers the background information of the concepts that have been applied. It gives brief description on the concepts of passive distributed antenna systems, swarm intelligence, Prufer code, and Particle Swarm Optimization. Chapter 3 covers previous works done to optimize the deployment of DAS and other traditional methods that have been researched or implemented. In chapter 4, we reduce the complexity of passive DAS inside the building by dividing the topology into inter floor and intra floor and optimize each of these deployments separately. we reduce the tree to Prufer code and then develop the PSO algorithm. In chapter 5, we evaluate the stop criteria for the algorithm. We also test the model to check how it reduces the cost of the cost of implementation of optimal DAS. The PSO also reduces the time it takes to develop a optimal DAS. We compare the hybrid approach taken by this work to taking a complete PSO approach. Chapter 6 finally concludes the work done and findings.

Chapter 2

Background

This section covers the basic concepts that have been used in this work. The topics that are explained are Distributed Antenna Systems, and Particle Swarm Optimization.

2.1 Distributed Antenna Systems

To provide indoor coverage, there are many different approaches available, which are passive and active distribution, hybrid distribution, repeaters and small cell. The approach selected for an application depends on down link power on the antennas and noise loss in the up link and down link[18]. The passive distributed antenna systems have been deployed since 2G. Figure 2.1 shows the topology of deployment of passive DAS in indoor buildings. In passive distributed antenna systems, unlike CAS, the antennas are geographically distributed hence replacing a central high power antenna with several low power antennas. These antennas are connected to the eNB/indoor base station using RF coaxial cables. The indoor base station is connected to the mobile switching center with an optical fiber.

The major advantages of passive DAS is that they are easy to design, they provide high data rates if the radio link is of good quality, and can be installed in harsh environments. The passive DAS uses simple passive components like splitters, coax cables, attenuators, tappers, and terminations[18]. Figure 2.2 shows that various Microlab components for

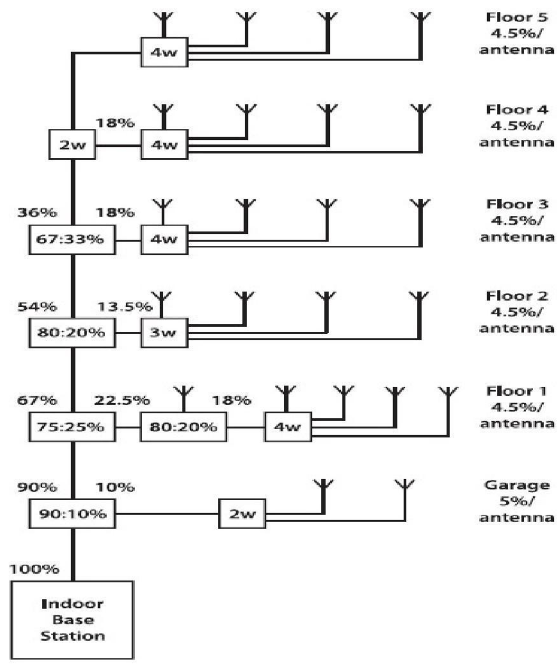

Figure 2.1: In-door Passive Distributed Antenna Systems

passive DAS deployments. The disadvantage of passive DAS is that although it is easy to design, the link budgeting can be a time consuming process. Also, there are high losses in the passive systems at each node of the topology which increases the noise figure of the base station at high frequencies. The cost of upgrading a passive DAS network is high too as it requires almost complete overhaul of the network.

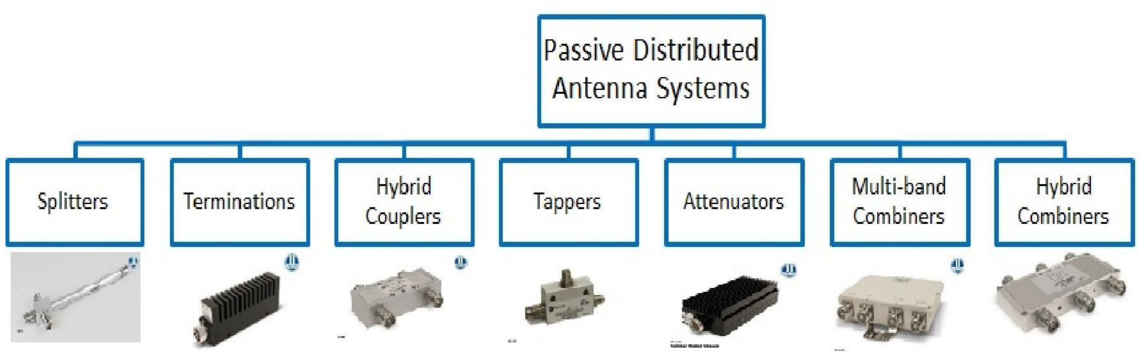

Figure 2.2: Passive Distributed Antenna Systems Components

2.2 Particle Swarm Optimization

Particle Swarm Optimization(PSO) is a stochastic global optimization algorithm based on the concept of swarm intelligence. The global optimization algorithms converge well to the global optima with lack of theoretical confirmation[9]. Swarm intelligence principle is the collective co-operation of multiple entities to achieve desired result instead of a central controller that defines the behavior. The swarm intelligence is exhibited by the smaller insects or flocks of birds when they travel[4]. The insects individually are not capable enough however, in swarms, due to their collective intelligence, they can achieve results far beyond their capabilities. PSO is a stochastic algorithm that solves an optimization problem in a search space or model and predicts the result bound by objectives[15]. For eg, the algorithm would choose the correct splitters and their placements in the space for the cheapest topology and meeting the antenna specifications. This is achieved by moving around the splitters and trying the different types of splitters which is called changing the velocity. We can apply the concepts of PSO to optimize the design of passive DAS, for a cost efficient solution. The basic elements of PSO algorithm are explained in [17]. The PSO offers significant advantages over other optimization algorithms as it requires less parameters to be changed and also the convergence of this algorithm is much quicker than other algorithms[5].

To be able to apply PSO algorithm to a DAS tree, we need to reduce the DAS tree into a Prufer Code. The Prufer code is a unique sequence of digits that can completely define a tree topology. Any Prufer code can be converted into a tree and any tree can be translated to Prufer Code. The Prufer code for a given tree topology is unique and hence not ambiguous. Therefore, a tree will have only one unique Prufer code and a unique Prufer code can only generate a unique topology of a tree[12]. The Prufer code consists of n-2 elements, where n are the number of nodes in a tree. This shows us that all the tree topology with nodes n can be denoted by all the n-2 element Prufer codes belonging to the set $\{1,....,n\}$. This is advantageous as the Prufer Code is able to map all the valid tree topologies in the n-2

Splitter Type	2-way	3-way	4-way	6-way	8-way
Cost	$54.67	$62.67	$66.67	$105.33	$140.00
Split Loss	3dB	4.8dB	6dB	7.8dB	9dB
Max. Insertion Loss	0.4dB	0.5dB	0.6dB	1.0dB	1.0dB
Amplitude Balance	0.3dB	0.6dB	0.3dB	0.8dB	0.8dB
VSWR All Ports	1.25:1	1.30:1	1.25:1	1.40:1	1.40:1

Table 2.1: Cost Comparison of different splitters

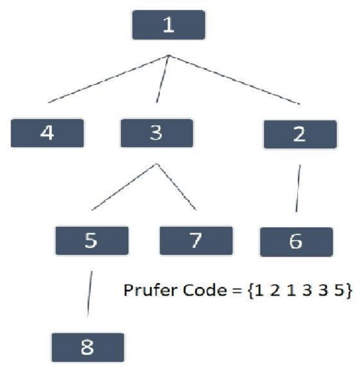

Figure 2.3: Tree Diagram of a Prufer Code

Euclidean space, which makes it possible to use PSO and other optimization algorithms for optimization of the tree. Figure 2.3 provides the tree diagram of a given Prufer Code. The method to convert a Prufer code to tree and vice versa is provided in [12]. The algorithm to convert a Prufer Code to tree diagram is[16]:

- **Step 1 :** Write down n numbers{1,....,n} which would be your list.
- **Step 2 :**Choose the smallest number x from the list which is not in the Prufer Code.
- **Step 3 :**Choose the first number y of the Prufer Code and join the two nodes of x and y and remove them from their corresponding segments.
- **Step 4 :**Check if there are only two number remaining in the list. If yes, join the two nodes of the numbers remaining and your tree is complete. If no, then go back to the bullet 3 and repeat the instruction until there are only two numbers left in the list.

Chapter 3

Literature Survey

We have established the methodology that we will be using to solve the focus of this work. According to [13], the deployment of passive DAS has high Total Cost of OwnershipTCO. Figure 3.1 depicts the cost of deploying DAS with respect to the area of coverage[13]. Although, it can vary significantly based on whether the region is a developed or a developing country. This is mainly due to the costs of labor being lower in developing nations. The TCO is high for passive DAS because the cost of installation and network planning is high. In addition to this, the cost of deployment is also high for passive DAS, which is due to the high costs of cables per meter and high cost of splitters that are a significant part of passive DAS network. Table 3.1 illustrates the costs of splitters. Therefore, to reduce this cost, it is imperative to design the passive DAS network optimally. The optimization of design in passive DAS is easier said than done[7]. The complexity of design is On^{n-2} in number of network nodes. This makes most algorithms of optimization very limited in the number of nodes or size of the deployment[7]. A lot of work has been done to implement multiple traditional optimization algorithms which are provided in the next section[6].

The deployment of passive DAS inside the buildings has been analyzed in [10]. According to [10], the use of just outbuilding coverage would allow the users on the high end of the building to receive better coverage than the users on the lower levels. However, im-

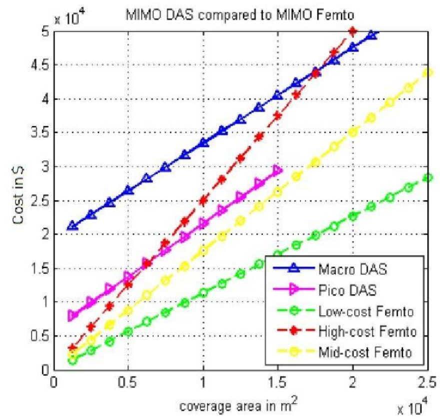

Figure 3.1: Total Cost of Ownership over a period of 7 years

plementation of in-building DAS improves the overall coverage and data speed of everyone, the users on the lower levels would now experience better service than higher level users due to difference in interference[2]. [11] investigates the impact of the location of antenna in in-building passive DAS. The Received Signal Code Power*RSCP* average increases if the number of antennas are increased in an open area inside the building and closed corridors. The application of Mixed Integer Linear programming method to the optimization of the passive DAS deployment was explored in [7]. The objective of was to reduce the deployment of cables and hence reducing the cost of deployment of DAS. The model had several limitations like the type of splitters and the individual antenna power requirements. The model can only be used to optimize if the deployment is on the single floor which is called intra-floor coverage. [1] applied the concepts of pseudo-polynomial time algorithms and fully-polynomial time approximation. The paper showed that they were able to achieve near optimal solution for the deployment. This method does not focus on reducing the cable cost but rather, they have assumed that the antennas are already optimally installed and the main idea was to optimally select the appropriate splitters to reduce the antenna power deviation. [3] applies the genetic algorithm*GA* to the problem of optimizing DAS design. The approach is to use variable power antennas instead of uniform power antennas for the design. This optimizes the location and design to use less number of antennas. They also validate that the amount of power leakage is lesser in the entire network.

Chapter 4

Optimal Model Algorithm

Now we define the model that we will be implementing to find a solution to the problem statement. As explained in Chapter 2, the in building DAS design that we are trying to optimize considers cost and coverage area. The in building DAS visualization showed in Figure 4.2[19], the model that we will be using for the focus of this work. In this passive DAS system, to optimize this complex network design for minimal cost in deployment and meeting all the network requirements is too complex. Hence, we divide the design into two different sectors and optimize each of them individually. The division and reduction in complexity of the optimization problem allows us to convert the tree into Prufer strings and use the PSO algorithm in a better way than traditional methods. The divisions are intra floor DAS and inter floor DAS.

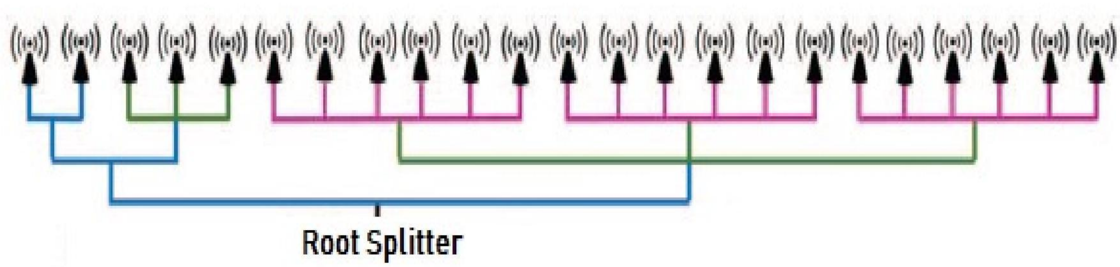

Figure 4.1: Large Splitter Tree for Intra Floor DAS

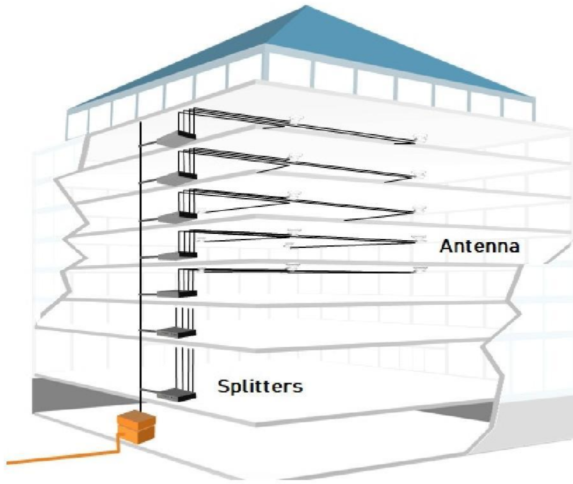

Figure 4.2: In-building DAS Visualization

4.1 Intra Floor DAS

This is the topology of DAS limited to the floor. The source splitter is considered the root of the tree topology and the antenna are the leaves. The co-axial cables connecting the nodes and antennas make the branches. An optimal topology would be the one where all the antennas receive the desired power level with minimal cable lengths and splitters. We can determine the minimum power that the root splitter at each floor would require by summing the antenna power requirement with the worst path sum of losses at each node that cascade and the cable loss. This is a simple calculation. We can inherently see that using the highest available splitter would reduce the layers in the tree. Also, the number of nodes would be lesser than using smaller splitters. The diagram of the deployment is depicted in the Figure 4.1. This leads to a straight conclusion that a tree deployment with largest splitters will have the least losses. In evaluating costs, we can see from Table 2.1, that using one 8-way splitter for 8 antennas on one floor would cost $140 compared using four 2-way splitters or two 4-way splitter and a 2-way splitter.

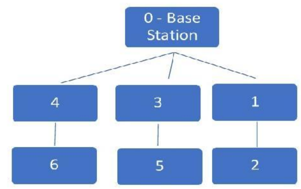

Figure 4.3: Inter Floor DAS Tree

4.2 Inter Floor DAS

This is the topology of DAS connects between floors. We can treat the inputs to the splitters of each of the floors as antennas and design the network. This reduces the floor into a node and the node would have its own power matching parameters like an antenna. The deployment can be visualized as a tree spanning from the base station to the nodes of each floor and the design of this tree needs to optimal to incur minimum cost of splitters, cables, and meeting the desired power of each floor node.

As can be seen from the Figure 4.2, the base station can be represented by the root of the tree with the index 0 and the rest of the floor nodes can be indexed upwards. The tree representation of the topology is shown in Figure 4.3. The topology of the tree does not necessarily always resemble to the Figure 4.3, however, we use PSO to optimize any tree topology. Since, we now have the tree topology, to apply swarm intelligence, we need to first covert the tree into a Prufer code. Prufer code has been explained briefly in section 2.2 but we will delve a bit deeper to apply it to our focus of work. The Prufer code can uniquely represent any tree with n nodes with n2 elements in Prufer Code. Figure 2.3 shows a tree that has been represented by the Prufer Code. The Prufer Code elements are the indexes of the nodes of the tree they represent. Since our tree has 6 nodes, the Prufer Code that we will have will be of 4 elements$\{1,.,.,n\}$. The major advantage of converting to Prufer Code is that it is able to map tree into Euclidean space which is compatible with swarm intelligence algorithms. Interconversion between trees and Prufer code is provided in detail in [12].

4.3 Particle Swarm Optimized Design Model

The inter floor tree has already been optimized with the use of tradition methods. This is so because in terms of coverage, it is assumed that the antenna locations are fixed and hence, the choice of splitter and topology were the only governing factors that could be optimized which have been done so in Section 4.1.

We now move ahead with applying the Particle Swarm Optimization to the inter floor DAS Prufer code under necessary constraints. In PSO, the nodes can move in the euclidean space along the direction that can be defined by any or all of the axes. The movement of the node can vary in velocity. Therefore, we need to define the euclidean space such that, any node at any point in the space is a real solution that can be deployed. Each node exploring in the euclidean space allows to find the optimal topology quickly and much more easily than traditional optimization algorithms. The swarm intelligence has been similarly used to optimally solve problems like traffic control, network routing etc. When the nodes are exploring in the Euclidean space, the algorithm stores the optimum solution for the individual node and the optimum solution for the swarm of nodes. Eventually, the directions and velocity are directed towards the two optimum solutions which makes the algorithm converge on the single global optimum solution. The possibility for the nodes to traverse in Euclidean space is what allows PSO to gradually converge on the optimum solution.

Our simulation, considers a n-level building, with the topology tree represented by n-2 Prufer code elements where n are the indexes of the floors. We limit the Euclidean space to n-2 dimensions as we want the global optimum to be physically realizable. The velocity of traverse of the nodes is randomly kept within the range $r_{min} - r_{max}$ to achieve a global optimum efficiently. To prohibit the nodes from ending up at the edge of the Euclidean Space, MATLAB implements a rule to reverse the direction of the node when it reaches the defined space boundaries. At every position the node takes, the information is stored to first check if the appropriate power will be delivered to the floor node and then check the cost to implement it. This would be done for both the individual node and the swarm of nodes. We know the minimum power level required by the floor node from the worst path loss of the intra floor DAS as discussed in Section 4.1. Next, the algorithm determines the complete required power for the DAS system and check it with the power provided by the base station. If the total DAS power requirement is higher than the base station power then the topology is rejected. Although, if the power requirement is less than that provided by the base station then the topology is saved for further consideration with costs. The algorithm is constrained by the power requirements of the antennas in the intra floor DAS. Also, since the splitter outputs cannot be left open, it adds another constraint to the algorithm. The fitness function is then calculated which is the total deployment cost for the DAS. Thus, we get the complete topology and we are able to develop a PSO passive DAS model for in building coverage. The algorithm takes advantage of the two modes of PSO, in MATLAB, which are exploitation and exploration mode[8].

$$F = TotalCableLength.Cablecostpermeter + \sum Totalnumberofsplitters.CostofeachSplitter$$

$$= L_{Cable}.C_{\$\{\}m} + \sum N_{Splitters}.C_{Splitter}$$

The maximum inertia range α is sum of 0.5 and random number between -0.5 & +0.5. This allows the value of α to be in between 0 and 1. In the exploitation mode, the value of α is between 0.5 and 1, and in exploration mode, α is between 0 and 0.5. y_1 and y_2 are the adjustment weights that are called Self Adjustment and Social Adjustment Weights respectively.

function(N,S) = particleswarm-model(Nodes, Floors)

for node i

Initialize random position vector $x_i \in 1, .., n$;

Initialize random velocity $r_i \in r_{min}, .., r_{max},$;

Initialize best positions and cost $p_i \leftarrow x_i$, $F_i \leftarrow \infty$;

Initialize global best position and cost $g \leftarrow x_i$, $F \leftarrow \infty$;

While(stopping criteria not met)

for node i:

if x_i passes power limits then

Evaluate fit and cost function $F(x_i)$

if $F(x_i) \leq f_i$ then $p_i \leftarrow x_i$, f_i ¡ $F(x_i)$

if$_i \leftarrow F$ then $F \leftarrow f_i$, $g \leftarrow p_i$

for each dimension d = 1,...,n—2 do

$v_{i,d} = \alpha.v_{i,d}+y_1u_1(p_{i,d}—x_{i,d})+y_2u_2(g_i,d—x_i,d)$

Update particle's position $x_i \leftarrow x_i + v_i$

Algorithm 1: Optimized Passive DAS model code

Chapter 5

Results

In this chapter, we carry out experiments to check the optimality of the model and also record the results.

5.1 Algorithm Termination

We need to define a stopping criteria for this algorithm. This is so that the algorithm does not keep on running without us getting any fruitful return. There are various metrics that can be considered as the test to decide whether the algorithm should be stopped or not. MATLAB provided solution of MaxStallIteration which stops the algorithm when the relative change in the objective function is very insignificant. There are other tools provided by MATLAB for stopping the PSO . The other way to stop the algorithm is by setting a max number of iteration. This work does not chose this as it is time inefficient. If the model achieve optimal solution quickly, the algorithm still does not stop to complete the number of iterations set.This work uses the MaxStallIteration.

The program is run for 20 times with the inter-floors being randomized in the range of 5-50 floors that need coverage. The plot for the probability change to the previous model is provided in Figure 5.1. The plot shows that after 10 runs, the best possible solution has been obtained and the further details would hardly bring significant changes to the performance.

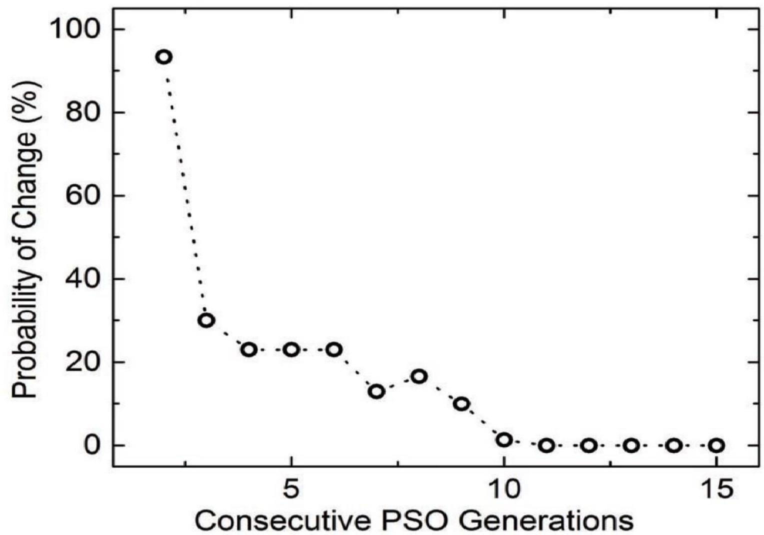

Figure 5.1: Probability of Change between PSO generated models

Therefore, we can take this to be the stopping criteria for the algorithm. Although, it may not be theoretically sound however, we can prove experimentally that this is an appropriate measure.

5.2 Time Comparison

Due to the complexity of the optimization problem for the inter floor DAS, which is in the order of O(n^{n-2}), this code was able to asses up to a 7 floors. The exhaustive search for the best deployment solution for a similar scenario would take 20 minutes however, using the PSO we are able to achieve this within 34 seconds. The shorter time is due to the linearity of the model. An exhaustive search for even taller buildings would rise exponentially for every extra floor to evaluate. The same is true for this model too however the model still is significantly quicker than exhaustive search. The brute force search would take couple of years to evaluate and come up with a optimal solution for building higher than ten floors due to a huge interval size of millions and no intelligence involved in the search. Therefore, this model is better than exhaustive search while also providing an optimal solution. The swarm intelligence significantly reduces the interval size and also the unnecessary computations.

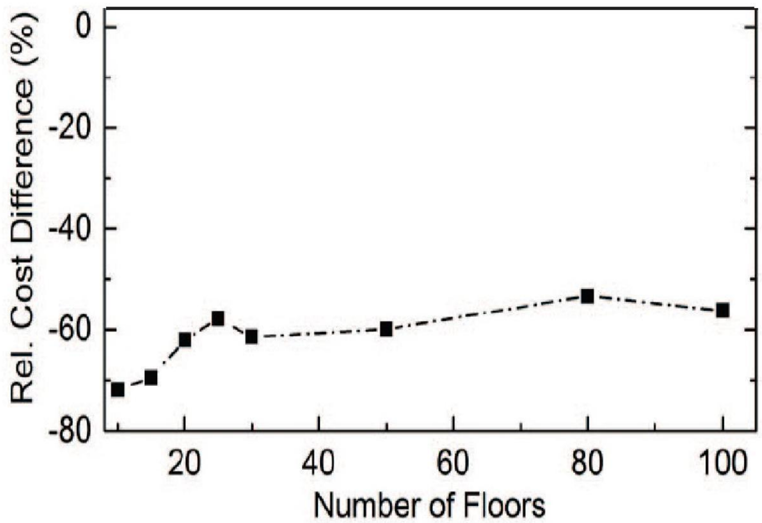

Figure 5.2: Relative comparison of cost for different number of floors

5.3 Power - Cost Trade Off

The PSO model is constrained by the power requirements of the nodes of the network. The cost of the network includes many different cost like CAPEX(Captial spent on assets), IMPEX(Cost of moving the equipment if necessary and planning), and OPEX which is straight forward the cost incurred in the day-to-day operations. The most significant costs are those of the equipments like splitter and cables. The power consumption and the equipment cost are two contradicting evaluations and one cannot be reduced without increasing the other. To meet the power constraints, it is necessary to keep the losses in the transmission as low as possible which would require better quality cables and more expensive splitter equipment. Its a good thing that for the most part, making a decision on the arbitrary trade off between the two is depended on the owner or the management team of the building.

5.4 Model Analysis

This section will explain the difference between the initial model generated and the final optimal model that it converges on. The best model from the all the initial models that are

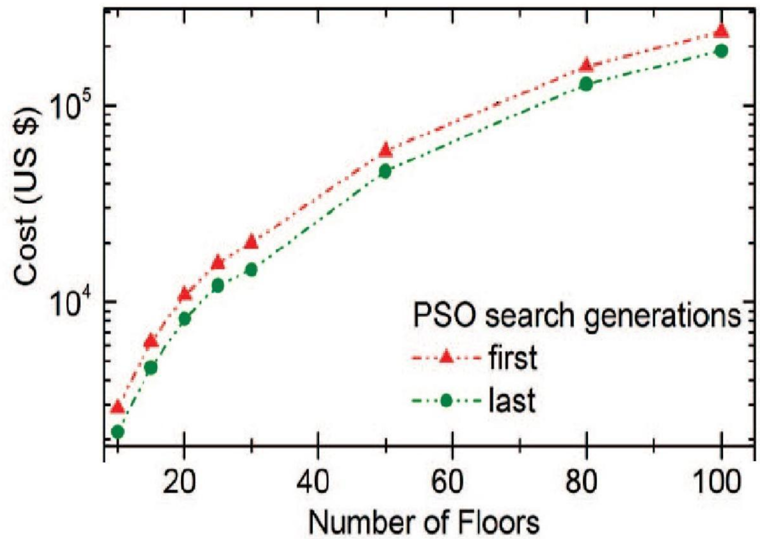

Figure 5.3: Comparison of cost between First and last model generated by algorithm

generated is taken for comparison with the final model.Figure 5.2 shows the relative cost comparison between the models generated. Figure 5.3 shows this for the buildings up to 100 floors. We can see that the difference in costs is significantly high at 50-60%. We can also see from the plot that the rate of improvement in the less floors is good. This is because the in less number number of floors, the influence of power requirement constraint is not significant. However, if we increase the number of floors then the power requirement constraint becomes significant which leads to less gradual improvement.

5.5 Comparison with complete PSO Approach

In our approach, we apply PSO to only the inter floor DAS and the intra floor DAS arrangement is developed by traditional heuristic method discussed in Section 4.1. However, we can apply PSO approach to intra floor DAS deployment too. Figure 5.4 shows the cost difference between complete PSO approach and our hybrid approach. We can see that the cost difference between complete PSO approach and hybrid approach is not significant. However, the computing time for complete PSO approach is significantly higher. This is because the complete PSO approach has a larger size of solutions. The larger size is due to

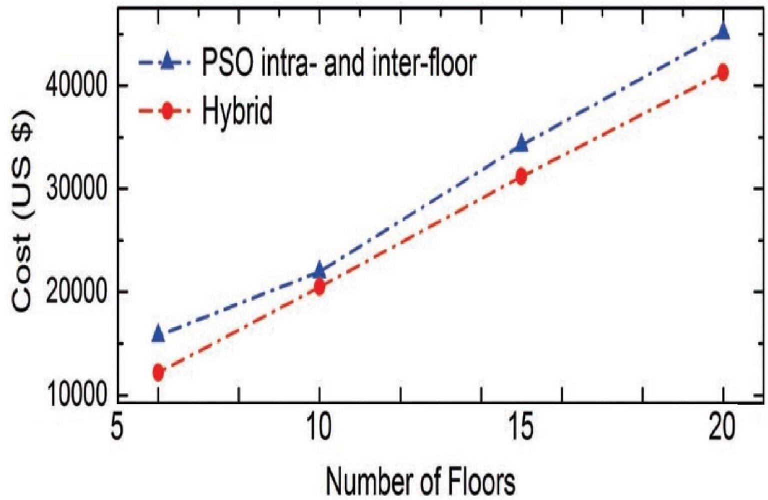

Figure 5.4: Comparison of costs between complete PSO and hybrid

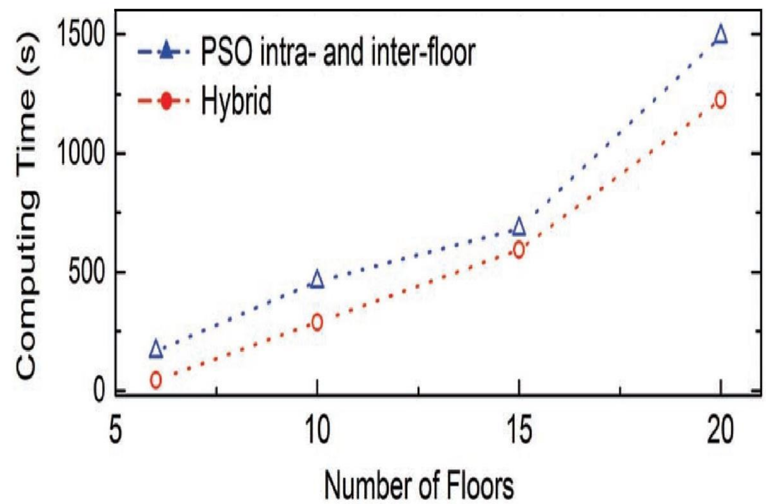

Figure 5.5: Comparison of Computing Time

the assumption that the antenna positions are not fixed and dynamically allocated based on the PSO algorithm. Figure 5.5 shows the significant difference in computing time for the complete DSO and hybrid approach. The extra computing time is not warranted by a better performance of DAS.

Chapter 6

Conclusion

This work proposes the use of Particle swarm optimization for a time and cost economical approach to design of passive DAS. The huge complexity of design of DAS was initially broken down to inter floor and intra floor DAS systems. We applied heuristic approach for the design of intra floor DAS and PSO to the inter floor DAS. The heuristic approach assumed that we have fixed antenna locations for intra floor DAS. The hybrid approach is used to significantly reduce the computing time for optimal DAS deployment and also to reduce the cost of equipment like splitters and cables. In application of PSO, we have first reduced the tree to a Prufer code to ensure compatibility with the PSO algorithm. We developed a PSO algorithm with the necessary constraints of in-building passive DAS like power requirements of each node. Once, the model was complete, we developed a stopping criteria for algorithm which significantly reduces the computing time. The test results of this showed us that we are able to achieve optimal DAS design in extremely reduced time when compared to brute force search. The reduced time is achieved because of swarm intelligence which significantly reduces the interval size. We also compared the hybrid approach to applying PSO to both inter and intra floor DAS. The comparison showed us that the all-PSO approach takes more computing time and also limits the performance of the DAS due to several constraints making it a sub-optimal design.

Bibliography

[1] D. Adjiashvili et al. "Exact and Approximation Algorithms for Optimal Equipment Selection in Deploying In-Building Distributed Antenna Systems". In: *IEEE Transactions on Mobile Computing* 14.4 (Apr. 2015), pp. 702–713. ISSN: 1536-1233. DOI: 10.1109/TMC.2014.2331976.

[2] T. Alade, H. Osman, and M. Ndula. "In-Building DAS for High Data Rate Indoor Mobile Communication". In: (May 2012), pp. 1–5. ISSN: 1550-2252.

[3] R. Atawia et al. "Indoor Distributed Antenna System Planning with Optimized Antenna Power Using Genetic Algorithm". In: *2013 IEEE 78th Vehicular Technology Conference (VTC Fall)*. Sept. 2013, pp. 1–6. DOI: 10.1109/VTCFall.2013.6692238.

[4] Christian Blum and Daniel Merkle. *Swarm intelligence: introduction and applications*. Springer, 2010.

[5] C. H. Chen et al. "PSO and APSO Evolutionary Computing in Indoor Wireless Communication". In: *2012 Sixth International Conference on Genetic and Evolutionary Computing*. Aug. 2012, pp. 204–206. DOI: 10.1109/ICGEC.2012.122.

[6] L. Chen and D. Yuan. "Design of in-building distributed antenna systems: Mathematical models and efficient algorithms". In: (June 2015), pp. 1497–1502. ISSN: 2164-7038.

[7] *Mathematical modeling for optimal deployment of in-building Distributed Antenna Systems*. Aug. 2012, pp. 786–791. DOI: 10.1109/ICCChina.2012.6356992.

[8] *Documentation*. URL: https://www.mathworks.com/help/gads/examples/optimize-using-a-particle-swarm.html.

[9] K. Hatalis et al. “Particle swarm based model exploitation for parameter estimation of wave realizations”. In: *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*. Dec. 2016, pp. 1–8. DOI: 10.1109/SSCI.2016.7850260.

[10] K. Hiltunen, B. Olin, and M. Lundevall. “Using dedicated in-building systems to improve HSDPA indoor coverage and capacity”. In: *2005 IEEE 61st Vehicular Technology Conference*. Vol. 4. May 2005, 2379–2383 Vol. 4. DOI: 10.1109/VETECS.2005.1543761.

[11] Tero Isotalo, Jarno Niemelä, and Jukka Lempiäinen. “Measurements for Distributed Antennas in WCDMA Indoor Network”. In: 2006.

[12] Bryant A. Julstrom. *Quick Decoding and Encoding of Prüfer Strings: Exercises in Data Structures*. 2005. URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.36.6484&rep=rep1&type=pdf.

[13] Z. Liu et al. “Economical Comparison of Enterprise In-Building Wireless Solutions Using DAS and Femto”. In: (Sept. 2012), pp. 1–5. ISSN: 1090-3038.

[14] Microlab. URL: https://microlabtech.com/das-applications/.

[15] Andrea E. Olsson. *Particle Swarm Optimization: Theory, Techniques and Applications*. ProQuest Ebook Central: Nova Science Publishers, Inc., 2011.

[16] *Prüfer sequence*. Aug. 2017. URL: https://en.wikipedia.org/wiki/Pr%C3%BCfer_sequence.

[17] J. Robinson and Y. Rahmat-Samii. “Particle swarm optimization in electromagnetics”. In: *IEEE Transactions on Antennas and Propagation* 52.2 (Feb. 2004), pp. 397–407. ISSN: 0018-926X. DOI: 10.1109/TAP.2004.823969.

[18] Morten Tolstrup. *Indoor Radio Planning: A Practical Guide For 2G, 3G and 4G*. Chichester: John Wiley, 2015.

[19] JMA Wireless. *E-DAS - ENTERPRISE DISTRIBUTED ANTENNA SYSTEM*. URL: http://info.jmawireless.com/e-das-solution-paper-download?hsCtaTracking=e735f8c2-9692-4884-b106-50ea58dceb44%7C2d52ab56-eb84-43c2-84a6-b9496c1dd4f9.

Vita

Rohan A. Shah was born to Alkesh L. and Roopa A. Shah in Ahmedabad, India on September 30, 1992. He graduated from Delhi Public School, India and did his under graduation at University of Pune, India where he received the degree of Bachelor of Engineering in Electronics and Telecommunication Engineering in May of 2015. Between the Summer of 2015 and Fall of 2016, he was engaged in work at Motif Inc., Ahmedabad, India, where he worked on computer network systems. In Fall of 2016, he joined Lehigh University to pursue Master of Science in Electrical Engineering. In Fall of 2017, he interned at Wireless Telecom Group Inc., working on passive distributed antenna system deployment design. Mr. Shah has accepted a position as a Product Manager at Wireless Telecom Group Inc., Parsippany, New Jersey.